TWO-STEP WAVESTRAPPING: SIMULATING NON-STATIONARY ACCELERATION DATA IN THE MOBILE COMPUTING CONTEXT

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Abstract

Measurements of acceleration provide an important source of information in understanding and predicting the movements of mobile computer users. However, collecting acceleration data can require substantial time and resources because it involves both human participation and the construction of adequate contextual environments. Thus, simulating acceleration data would be helpful to circumvent these difficulties. However, using traditional resampling techniques turned out to be inadequate for simulation of these non-stationary time series data. The present study proposes a wavelet-based resampling approach, called the "two-step wavestrapping," which consists of parallel wavestrapping and energy/trend adjustments. This approach was applied to the acceleration data we collected from mobile computing users under six different contextual settings. The results showed that two-step wavestrapping can successfully generate surrogate acceleration data from the collected acceleration data.

1 Introduction

An accelerometer is an inexpensive, convenient, energy conservative sensor that can capture the acceleration of target objects. Many domains, such as medical engineering (e.g., [Kim et al., 2003, Uiterwaal et al., 1998]), gait analysis (e.g., [Clayton and Schamhardt, 2000]), and human factors (e.g., [Griffin, 1990]), have used it to infer the movement of subjects under investigation. Recently, it also has been used in understanding how users behave while they use mobile or wearable computers (e.g., [Crossan et al., 2005]). In this mobile computing context, various methods have been developed to recognize the behavioral patterns from acceleration data, but one crucial problem is that the results of these methods depend on the extent to which the collected data are representative and unbiased [Intille et al., 2004, Bao and Intille, 2004]. Collecting extensive data from a large population might be a way to enhance the accuracy, but collecting acceleration data from human subjects comes with associated time and resource costs. Thus, if simulating similar acceleration data is possible, the surrogate data could be used to test and enhance the robustness of these pattern recognition techniques at a relatively low cost. However, acceleration data are non-stationary, tri-dimensional, and time dependent. So, generating the surrogate acceleration data of mobile devices in use is not a trivial exercise [Angelini et al., 2005], meaning that some traditional methods of simulating or resampling data such as traditional bootstrapping are not successful.

Some recent efforts for developing resampling methods for time series data might be a solution to this problem. Such resampling methods typically exploit the whitening or decorrelation property of the discrete wavelet transform [Bühlmann, 2002]. However, adjacent wavelet coefficients may not be completely decorrelated, especially for strongly correlated time series data. Additionally, the stationarity of the wavelet coefficients is often broken after resampling. For these reasons, it may be necessary to place constraints on the type of resampling scheme that operates on the wavelet coefficients.

To resample weakly correlated data in the wavelet domain, one can use a stationary bootstrap approach rather than traditional bootstrap approaches. Provided that the block size is large enough to encompass the dependencies of the data, the correlations within each block are preserved, leading to an improvement in the overall preservation of the correlations among horizontally adjacent wavelet coefficients (i.e., within-level correlations) after resampling. Angelini and colleagues [Angelini et al., 2005] showed that block based methods outperform the simplest bootstrap methods because they preserve correlations in the wavelet based resampling scheme. However, the current wavestrap methods still have a limitation. Few studies to date take correlations of wavelet coefficients among different scale levels (i.e., between-level correlations) into account. Due to ignoring “the vertical correlations,” the surrogate data have less disruptive peaks than the original data do.

To overcome these limitations, we propose a two-step wavestrap technique. The first step is called “parallel wavestrapping,” which is a simultaneous stationary bootstrapping among different scale levels in order to preserve between- as well as within-level correlations. The second step is an adjustment procedure to make surrogate time series reflect the trend and scaling properties of the original acceleration data.

The organization of this article is as follows. In Section 2, several basic concepts of wavelet-based resampling approaches and the explanation of how we collected acceleration data are provided. In Section 3, using the collected acceleration data as an example, the limitations of the previous methods and the efficiency of the proposed methodology are described. Finally, the discussion and conclusions follow in Section 4.

2 Background

2.1 Bootstrapping

Bootstrapping [Efron, 1979, Efron and Tibshirani, 1993] was originally designed for independent, identically distributed (i.i.d) data to extract additional information (e.g., confidence interval of an estimator) from a single run of data. As an analogous technique, Theiler and colleagues suggested a surrogate data method which is basically the same as bootstrap method and mainly used for testing nonlinearity in observed time series data [Theiler et al., 1992]. In applying the bootstrap method to time series data, preserving the autocorrelations of the data is challenging because bootstrapping scrambles correlations between adjacent data points in the time domain. The most common way of avoiding this problem is to resample the observations in blocks of data points rather than in individual data points, which is called "block bootstrapping," [Künsch, 1989].

The underlying idea of the block bootstrap method is that if the blocks are long enough, the original dependencies or autocorrelations in the time domain would be preserved in the resampled time series data. Problems with block bootstrapping are: 1) The stationarity of time series data is often broken, and 2)the variability of samples decrease when the blocks are long. To overcome these problems, Politis and Romano proposed the stationary bootstrapping by taking blocks whose lengths, denoted as l, are geometrically distributed with density as shown in equation (1), and the start point of each block is selected randomly from the integers $0, 1, \cdots, n$, where n is the total length of the original time series data [Politis and Romano, 1994].

$$Pr(l = j) = (1 - p)^{j-1}p,\ j = 1, 2, \cdots . \tag{1}$$

This yields resampled time series data that are stationary with mean block length $1/p$. In practice, block resampling can still fail to preserve serial dependencies in the data, so that the resampled series are whiter than the original data [Davison and Hinkley, 1997]. Another solution is to resample the observed time series data after orthogonal transformation to another domain, which might have less serial dependencies. This approach will be discussed more in the following section.

2.2 Wavelets

Wavelets are orthonormal functional bases that have become increasingly important to researchers because of their several advantages over traditional techniques such as Fast Fourier Transform. Although the beginning of wavelets can be traced back almost a century, their widespread use began only about twenty years ago when new wavelet bases were discovered and their implementation was connected with fast-filtering computational procedures. Intuitively, the wavelet approach can be understood as a way of decomposing or atomizing the total energy or variance of time series data by an orthonormal basis of wavelets, each of which is weighted by a coefficient representing the amount of energy in the data at a particular scale and location. Through this decomposition or transform, wavelets offer the following characteristics [Vidakovic, 1999]:

- Locality of the analysis and ability to handle multiple scales
- Sensitivity to the fractal nature and self-similarity of data information
- Ability to minimize correlation and time-dependency of data
- Computational simplicity, which permits faster analysis
- Ability to remove noise from complex data sets

Locality is a useful characteristic of wavelets when sporadic or disruptive signals are analyzed. Unlike the sine or cosine waves of Fourier Transform, which extend infinitely with a particular frequency and phase, wavelets are finitely extended or compactly supported.

Wavelets are also sensitive to presence of scaling in data. In many natural phenomena and human activities, the behaviors at different scales are equivalent in a sense, and this can be expressed by a scale invariance property [Vidakovic, 1999]. Self-similarity is one of the most important random processes that can be used to model scale invariance and wavelet analysis has appeared to be a natural tool to reveal self-similar features due to their built-in multiresolution structure.

With the wavelet characterization of scaling processes, effective estimation schemes of scaling parameters were developed. The energies (squared wavelet coefficients) of the detail processes over all scales are second order descriptions of the process and, in total, constitute a wavelet spectrum. From a logarithmic view of the wavelet spectrum (e.g., the logscale diagram), the regular decay of average energies over some range indicates scaling with the slope giving the scaling exponent (see equation (2)). The logscale diagram was thoroughly investigated by Abry and colleagues [Abry et al., 2003, Abry et al., 1998].

$$log_2 E(j) = -aj + C, \tag{2}$$

where $E(j)$ is the average energy of jth scale, a is the slope, and C is a constant.

Other models exhibiting scale invariance, such as fractal, multifractal and $1/f$-like processes exist and can be analyzed in a common unifying framework by means of wavelets. For example, in case of fractional Brownian Motion parameterized by the Hurst exponent (H), the slope of logscale diagram is given by $a = 2H + 1$.

2.3 Wavestrapping

For certain classes of random processes, the wavelet transform whitens (decorrelates) the data [Bullmore et al., 2001, Bullmore et al., 2003]. That is, the correlations between the wavelet coefficients become small even if the signal itself is highly autocorrelated in the time domain [Beran, 1994]. In general, the correlation between wavelet coefficients decays rapidly with increasing number of vanishing moments of the wavelet filter. However, high-order wavelets with larger supports may produce more undesirable boundary artifacts. Hence, the choice of vanishing moments depends on the properties of the data, with few points for weakly correlated or short data sets and more points for strongly correlated or long data sets [Breakspear et al., 2003].

Due to this decorrelation property, the bootstrap method, which can cause problems in the time domain, can be used in the wavelet domain. Percival and colleagues proposed the wavestrap method, which proceeds by transferring the data to the wavelet domain, applying a resampling method, and then returning the resampled data as variants in the time domain [Percival et al., 1992].

Suppose that the number of data points is the power of 2, $n = 2^J$, and the original time series data $\underline{X} = \{X_1, \cdots, X_n\}$ are discrete wavelet transformed using an orthogonal wavelet basis with a finite number of vanishing moments. The wavelet transform of the series yields the scaling coefficients $\underline{c} = \{c_{J_0,0}, \cdots, c_{J_0,2^{J_0}-1}\}$ for a smooth part of the data signal and wavelet coefficients $\underline{d} = \{d_{J_0,0}, \cdots, d_{J_0,2^{J_0}-1}, \cdots, d_{J-1,0}, \cdots, d_{J-1,2^{J-1}-1}\}$ for a detail part of the data signal when the coarsest level of detail is set to J_0. To generate surrogate data, one can resample the wavelet coefficients, $d_{j,k}$, within each level j independently across the levels using the stationary bootstrap method, where $k = 0, \cdots, 2^{j-1} - 1$. In contrast, the scaling coefficients ($\underline{c}$) usually remain unaltered so that scaling coefficients preserve the main features in the original signal. After resampling, the scaling coefficients $\underline{c} = \{c_{J_0,0}, \cdots, c_{J_0,2^{J_0}-1}\}$ and resampled wavelet coefficients $\underline{d_b} = \{d_{bJ_0,0}, \cdots, d_{bJ_0,2^{J_0}-1}, \cdots, d_{bJ-1,0}, \cdots, d_{bJ-1,2^{J-1}-1}\}$, where subscripted b stands for "bootstrapping," are combined again and transformed back into the time domain ($\underline{X_b}$). Figure 1 shows the general procedure of wavestrap method and can be summarized as follows:

- Decompose the time series data into the wavelet domain using the discrete wavelet transform (DWT): $\underline{W} = DWT(\underline{X})$, where $\underline{W} = \{\underline{c}, \underline{d}\}$.

- Bootstrap the wavelet coefficients within each scale: construct $\underline{W_b}(j)$ from $\underline{W}(j)$, where j represents a scale level, where $\underline{W_b} = \{\underline{c}, \underline{d_b}\}$.

- Apply the inverse discrete wavelet transform (IDWT) to the resampled wavelet coefficients to generate a surrogate time series data: $\underline{X_b} = IDWT(\underline{W_b})$.

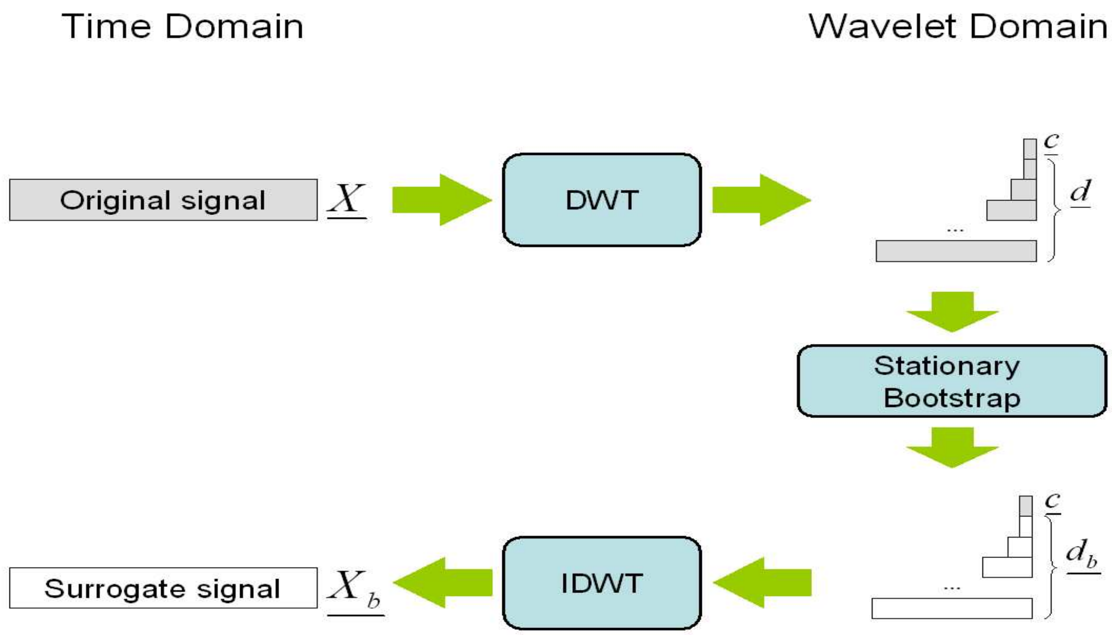


Figure 1: The procedure of the traditional wavestrap method.

Since the wavelet coefficients within a given level can show a small autocorrelation, one can use a stationary bootstrap approach in the second step to preserve the correlation structure. Ideally, the block size should be larger than the maximum lag for which the autocorrelation function is significant, and it has been shown that the choice $p_j \approx 2^{-j/3}$ is asymptotically optimal, where j is the scale level and p_j is the parameter of the geometric distribution for block lengths in the jth level (see equation (1)) [Fladrin, 1992, Mordant et al., 2003].

The choice of a wavelet filter is another important issue in wavestrapping. High-order Coiflets and Symlets wavelets perform comparatively to the Daubechies wavelets since both have similar support and smoothness. Resampling with Haar wavelets, which only have one vanishing moment, may not show a better fit of the spectrum. Other issues related to wavestrapping various data sets have been examined in more detail elsewhere [Andrzejak et al., 2004, Breakspear et al., 2003, Bullmore et al., 2001].

2.4 Acceleration data

As discussed in the Introduction section, simulating the acceleration data would be beneficial within mobile human-computer interaction research. Before the discussion of how to simulate the acceleration data in detail, we first describe how the original acceleration data were collected.

One hundred twenty six undergraduate students (mean age = 21.8 years) from the School of Industrial and Systems Engineering at the Georgia Institute of Technology participated in the study. Subjects were asked to perform reading comprehension tasks (i.e., reading ten passages on the PDA and answer two multiple-choice questions for each passage) on a personal digital assistant (PDA), the Palm™m505 (as shown in Figure 2). An triaxial accelerometer was attached to the back of the PDA to collect the acceleration data while a subject was performing the task. As shown in the figure, the x-axial acceleration indicates the left (-) and right (+) movement; the y-axial acceleration indicates the down (-) and up (+) movement; the z-axial acceleration indicates back (-) and forth (+) movement. For all three arrows, arrowheads indicate the direction of positive acceleration (+), and arrow tails indicate the direction of negative acceleration (-).

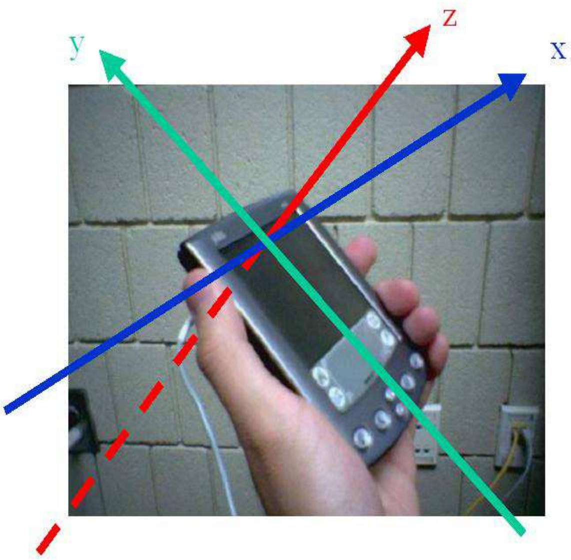


Figure 2: The PDA used for the experiment and three axes of the accelerometer.

In order to put the subjects under various contextual settings, two contextual factors (i.e., mobility and light) were manipulated as shown in Table 1. The mobility condition is a three-level between-subject factor, so each subject performed the task while he or she was sitting, walking on a treadmill, or following a path on the floor. The light condition is a two-level within-subject factor, so each subject performed the task under high light (approximately 260 lux) and low light (approximately 85 lux). The assignment of the mobility condition to each subject and the order of light conditions were randomized. These two contextual factors are known to affect the general patterns of acceleration data [Yi et al., 2005].

Table 1: Experimental factors

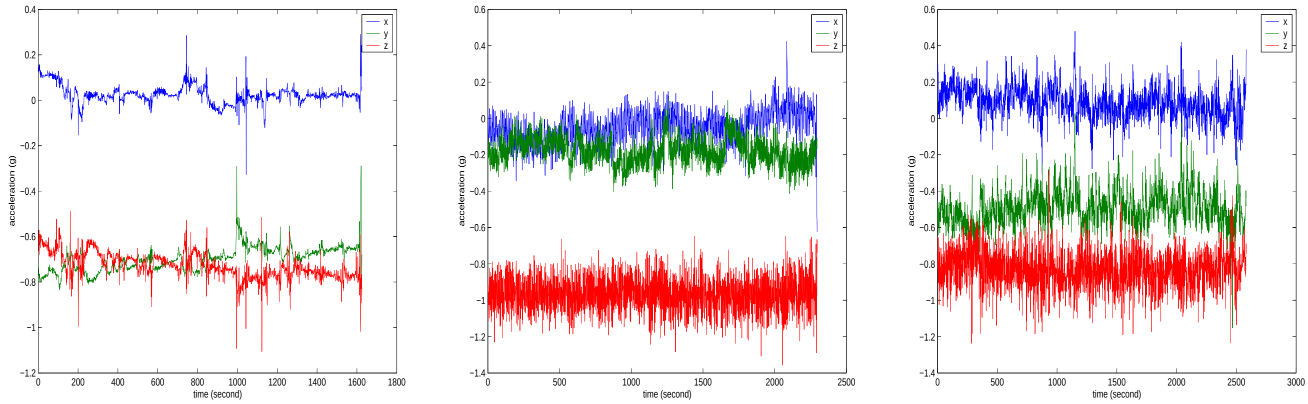
Mobility (Between-subject)	*Light* (Within-subject)
Sitting	Low light
Treadmill	High light
Walking	

Through the accelerometer on the back of the PDA, triaxial (x-, y-, and z-axis) acceleration data were collected at the frequency of 7 Hz. The examples of collected acceleration data from three subjects in different mobility conditions are plotted in Figure 3, in which x-, y-, and z-axial acceleration data are plotted in blue, green, and red, respectively. Besides the acceleration data, various other measures were collected as well, although the discussion of these are are out of scope of the present study. The results and analyses of these measures are discussed in other, related publications [Barnard et al., 2005, Barnard et al., ress].

3 Simulation

3.1 Data preprocessing

Before the collected data were used in the resampling procedure, some preprocessing steps were needed. The initial and ending parts of collected acceleration data had an additional noise due



(a) (b) (c)

Figure 3: The sample acceleration data: (a) sitting, (b) treadmill, and (c) walking. x-, y-, and z-axis acceleration data are shown in blue, green, and red, respectively.

to the movement associated with the startup and completion of the experimental procedure. The initial and final five seconds of acceleration data, comprising the head and tail of the data signal, were removed to avoid confouding from this experimental noise. The remaining data were not yet adequate for wavelet-based analyses because most wavelet-based approaches assume that data points are infinite or a finite size of 2^J. Therefore, to make the size of the acceleration data a power of two, we used the following rules:

- If (number of data points) < 1024, discard the data set.
- If (number of data points) $\in [1024, 2000)$, use the center 1024 data points.
- If (number of data points) $\in [2000, 2048)$, extend the data up to 2048 by flipping the tail of the data.
- If (number of data points) ≥ 2048, use the center 2048 data points.

Additionally, we realized that separating the signals into two parts, the high and low frequency parts, is useful in understanding the structure of the acceleration signal. The low frequency part shows the general trend of the signal, and the high frequency part shows the noise which is superimposed on the low frequency part. The threshold level between these two parts can be determined by visual inspection. Figure 4 shows an original acceleration dataset and several reconstructions of this acceleration dataset with different compositions of scaling and wavelet coefficients. For example, Figure 4 (a) shows reconstructed acceleration data with scaling and wavelet coefficients of scale level 3, when the coarsest level of detail was 3. As the number of scale levels used for the low frequency part increases, the reconstructed acceleration data have more details. We judged that the scaling and wavelet coefficients of scale levels 3 and 4 to be sufficient to show the trend of the acceleration data, which compose the low frequency part.

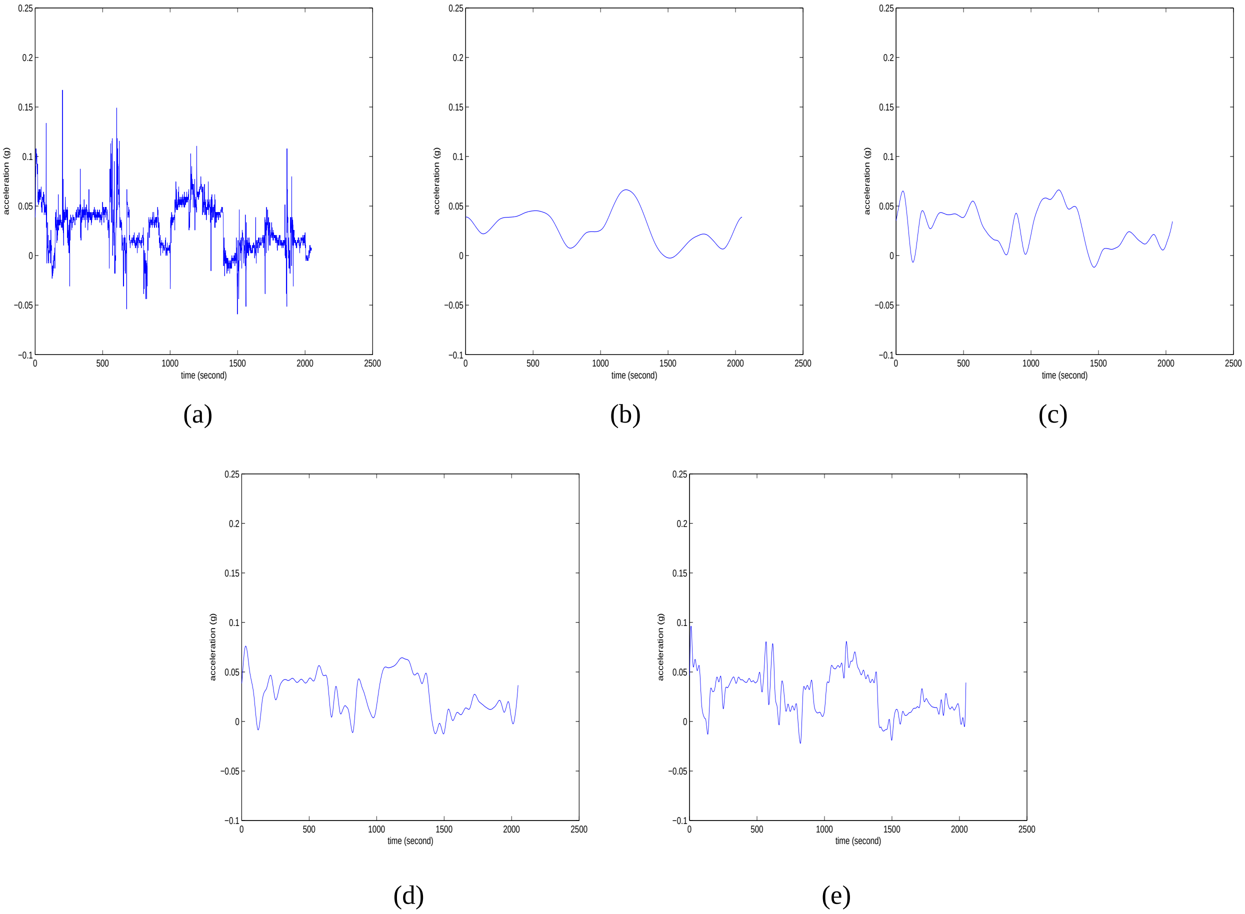


Figure 4: Reconstructed acceleration data with different scale levels: (a) original signal (b) scale level = 3 (c) scale levels = 3, 4 (d) scale levels = 3, 4, 5, and (e) scale levels = 3, 4, 5, 6.

3.2 Traditional method: wavestrapping

As discussed in the Background section, the basic idea of the wavestrapping is generating surrogate data by using the stationary bootstrap method in the wavelet domain, in which data are less correlated. Although wavestrapping is considered as a more advanced resampling approach than several bootstrap methods in the time domain, some critical problems still remain. These problems are demonstrated in Figure 5, which shows the difference in correlation patterns between original and wavestrapped wavelet coefficients. The original wavelet coefficients, shown in Figure 5 (a), contain cone-shaped patterns, indicating the existence of vertical correlations between scale levels, while the wavestrapped wavelet coefficients (shown in Figure 5 (b)) do not have these patterns. These cone-shaped patterns, known as ”cones of influence” [Vidakovic and Lozoya, 1998], provide evidence of correlations of wavelet coefficients among different scale levels.

These correlation patterns should be considered in generating surrogate data. Otherwise, the resulting time series data from the wavestrapped wavelet coefficients do not have as many peaks as the original data have (as shown in Figure 5 (c) and (d)). One possible solution for the problem is level-wise parallel stationary bootstrapping of wavelet coefficients. However, the number of wavelet coefficients for each scale level varies (i.e. 2^{j-1} for jth level), so this approach is cumbersome to implement. In order to circumvent this problem, we propose another resampling method, called “two-step wavestrapping.” As alluded by its name, it consists of two steps: the parallel resampling step and adjustment step (see Figure 6).

3.3 The proposed method: two-step wavestrapping

3.3.1 Methodology

As previously discussed, we used the ”two-step wavestrap” resampling method to generate the surrogate acceleration data as shown in Figure 6. In the first step, parallel resampling step, a one-step DWT is used instead of multi-step discrete wavelet transform. As alluded by ”one-

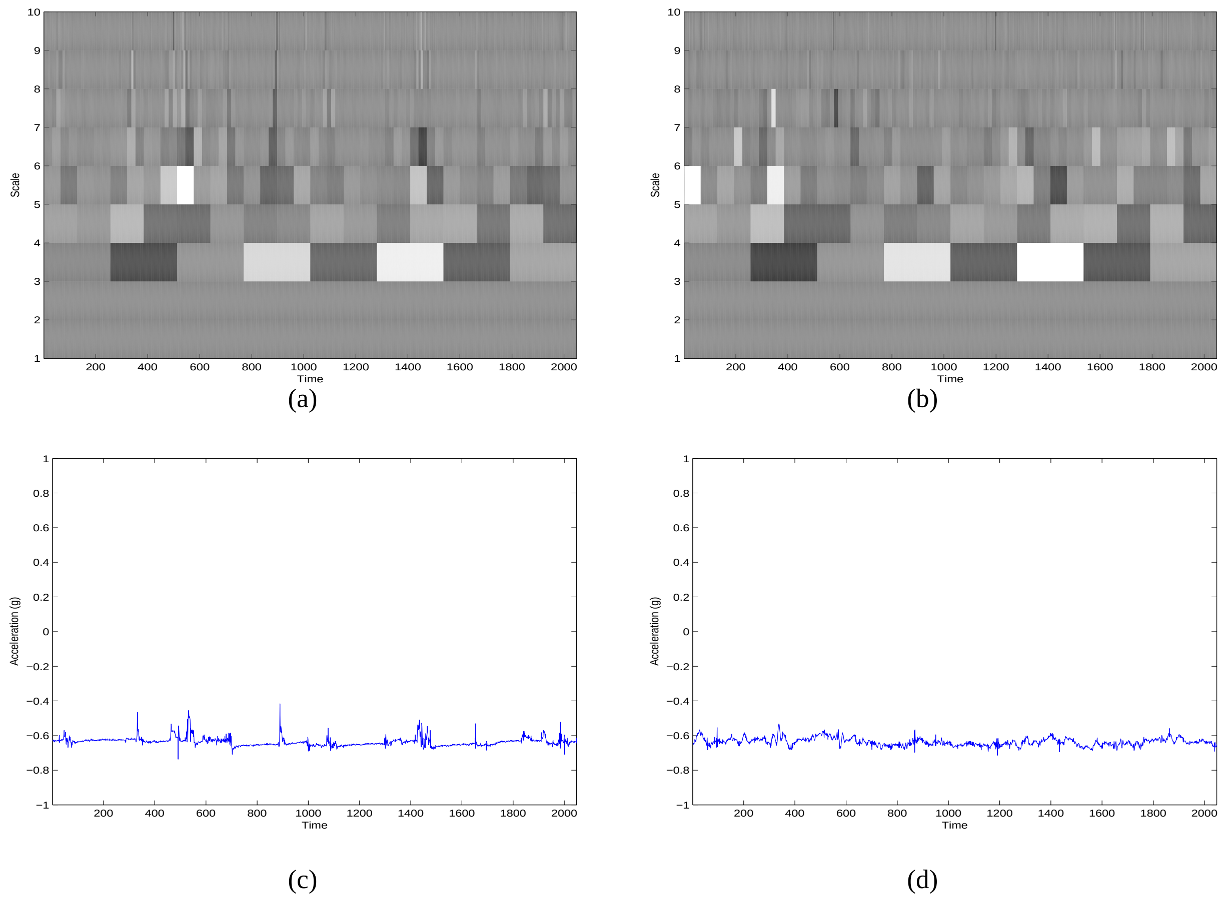


Figure 5: A comparison of (a) original and (b) wavestrapped wavelet coefficients and a comparison of (c) original and (d) wavestrapped surrogate time series data

step," this wavelet transform uses $J_0 = J - 1$ as the coarsest level of detail, so it generates the same number of scaling coefficients $\underline{c}^1 = \{c_{J_0,0}, \cdots, c_{J_0,2^{J_0}-1}\}$ and wavelet coefficients $\underline{d}^1 = \{d_{J_0,0}, \cdots, d_{J_0,2^{J_0}-1}\}$, where superscripted 1 stands for "one-step DWT." Since the numbers of scaling and wavelet coefficients are the same, applying a level-wise parallel stationary bootstrapping to the two sets of coefficients ($\underline{c}^1$ and $\underline{d}^1$) is possible. Because both of scaling and wavelet coefficients in the same time frame would be resampled together, the vertical correlations among levels are preserved. The resampled scaling and wavelet coefficients ($\underline{c}_b^1$ and $\underline{d}_b^1$) are used to obtain surrogate data ($\underline{X}_b$) using IDWT, where subscripted b stands for "stationary parallel bootstrapping." However, one problem of this step is that the main feature (or the general trend) of the original data were not preserved in the surrogate data since the scaling coefficients ($\underline{c}_b^1$) were scrambled in the resampling procedure. The solution to this problem lies in the next step of the procedure.

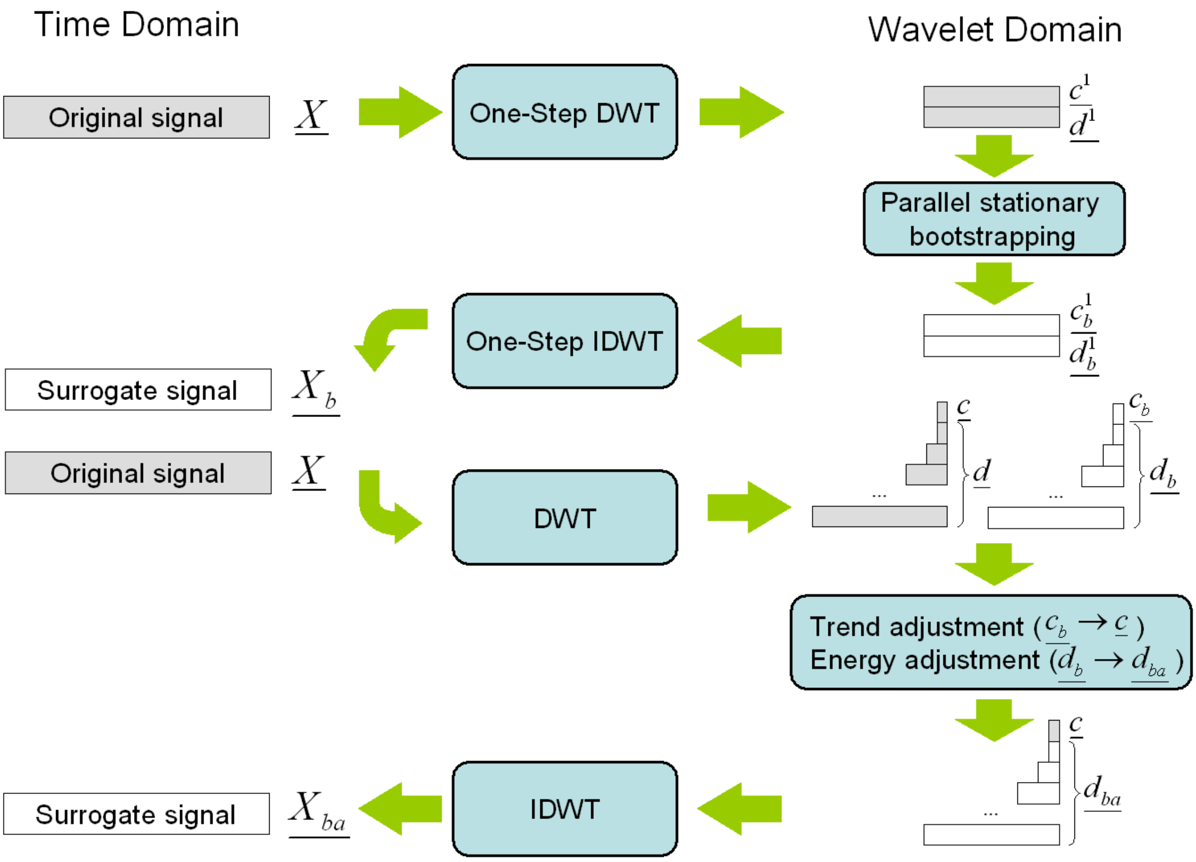


Figure 6: The procedure of the proposed two-step wavestrap method. Note: 1) The original data and its scaling/wavelet coefficients are colored in gray; 2) 'c' refers to scaling coefficients (the smooth part), while 'd' refers to the wavelet coefficients (the detail part).

The adjustment step, the second step, consists of trend and energy adjustments. In the trend adjustment, we apply another multistep DWT to both the surrogate data ($\underline{X}_b$) and the original data ($\underline{X}$). This second DWT generates two sets of scaling and wavelet coefficients for original data ($\underline{c}$ and $\underline{d}$) and surrogate data ($\underline{c}_b$ and $\underline{d}_b$). In order to revive the general trend in the surrogate data, the scaling coefficients of surrogate data ($\underline{c}_b$) is replaced with those of original data ($\underline{c}$).

Additionally, we take the energy adjustment for each scale level into account in the following steps:

1) Divide the subjects into l different groups ($G_L, L = 1, \cdots, l$), so that each group is characterized by statistically different scaling exponents (or Hurst exponents).

2) Calculate the group mean of average energy for each scale level of the original data. Let $\overline{e}_{(i)j}$ denote average energy of ith subject and jth scale level give by the following equation:

$$\overline{e}_{(i)j} = \sum_{k=0}^{2^j-1} \frac{{d_{b(i)j,k}}^2}{2^j}, i = 1, \cdots, N, j = J_0, \cdots, J-1, \tag{3}$$

where N is the number of subjects, and $d_{b(i)j,k}$ is the kth wavelet coefficient in the jth scale level of ith subject. The group mean of average energy of jth scale level ($\overline{e}_{(G_L)j}$) is given by the following equation:

$$\overline{e}_{(G_L)j} = \text{average}(\overline{e}_{(i)j}), i \in G_L, L = 1, \cdots, l. \tag{4}$$

3) Adjust the average energy for each scale level of the surrogate data to the group mean of average energy to accommodate the group scaling characteristics. This can be done by adjusting each wavelet coefficient ($d_{b(i)j,k}$) based on the square-rooted ratio of group mean of average energy ($\overline{e}_{(G_L)j}$) and the average energy of each subject($\overline{e}_{(i)j}$), so that the average energy of the ith subject based on adjusted wavelet coefficients ($d_{ba(i)j,k}$) conform to the group mean of average energy (see equation 5).

$$d_{ba(i)j,k} = d_{b(i)j,k} \cdot \sqrt{\frac{\overline{e}_{(G_L)j}}{\overline{e}_{(i)j}}}, i \in G_L, L = 1, \cdots, l. \tag{5}$$

Thus, the resulting scaling/wavelet coefficients ($\underline{c}$ and $\underline{d_{ba}}$) and surrogates ($\underline{X_{ba}}$), where subscripted a stands for "adjusted," preserve the vertical correlations among scale levels, the general trend of the original time series data, and the energy scaling characteristics of the group that each subject belongs to.

3.3.2 Results

Surrogate acceleration data can be simulated by the proposed two-step wavestrap method based on the collected acceleration data. First, we apply the parallel resampling step to the scaling and wavelet coefficients with geometric parameter $p = 0.1$ so that the mean block length is $E(l) = 1/p = 10$. Then, the resampled data are transformed back to the time domain, using IDWT. Figure 7 shows the low and high frequency parts of surrogate data generated from this step. The high frequency part of the reconstructed acceleration data shows some peaks and disruptive signals due to the parallel bootstrapping (the fourth row of Figure 7). However, the general trend of the original data is broken since the parallel bootstrapping resample of the scaling coefficients as well (the second row of Figure 7).

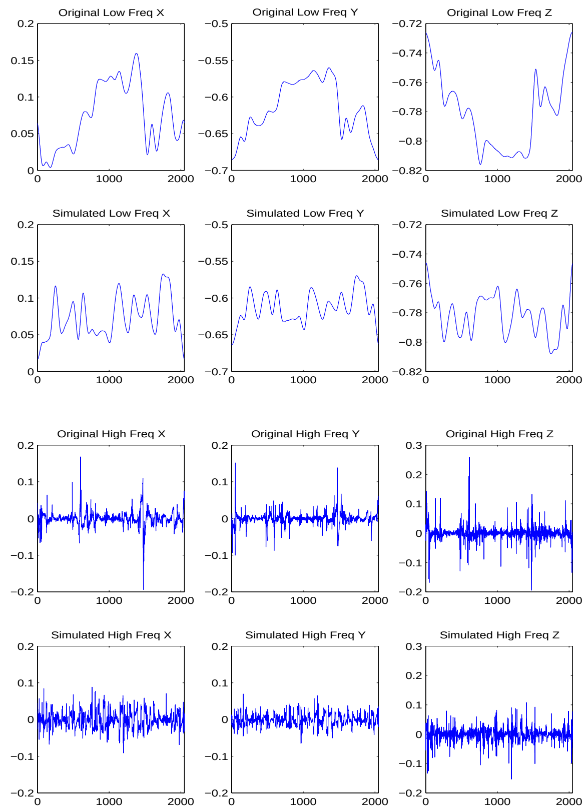


Figure 7: Original and simulated signal for a subject: the low frequency part (top six) and the high frequency part (bottom six).

As mentioned in the previous section, two types of adjustments are applied to the intermediate surrogate data. The first adjustment is replacing the scaling coefficients of surrogate data with those of original acceleration data. By doing this, the general trends in the low frequency part can be revived. The second adjustment is calibrating the energy scaling. Two contextual factors (i.e., mobility and light) are known to be influential to the acceleration data in mobile computing settings [Yi et al., 2005]. Thus, the acceleration data can be divided into six groups, since the mobility and light factors consist of three and two levels, respectively. The group mean of average energy for each scale level is calculated and logscale diagrams for each group are plotted in Figure 8.

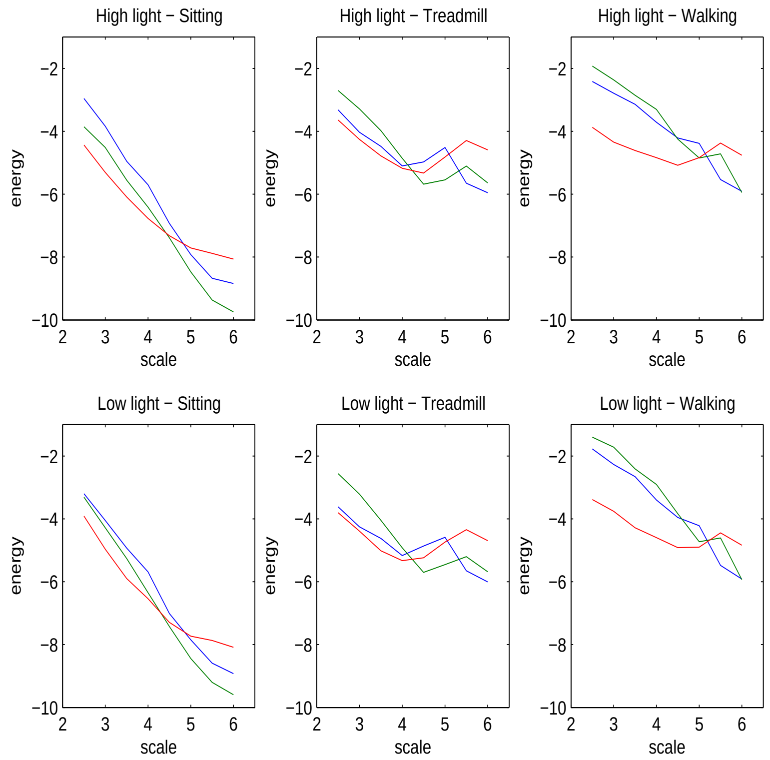


Figure 8: Logscale diagrams for each mobility and lighting condition. x-, y-, and z-axis acceleration data are shown in blue, green, and red, respectively.

The final result of the parallel bootstrapping and adjustment procedure is shown in Figure 9. As shown in the figure, the general trend is successfully recovered, so the resulting signal much better resembles the original signal.

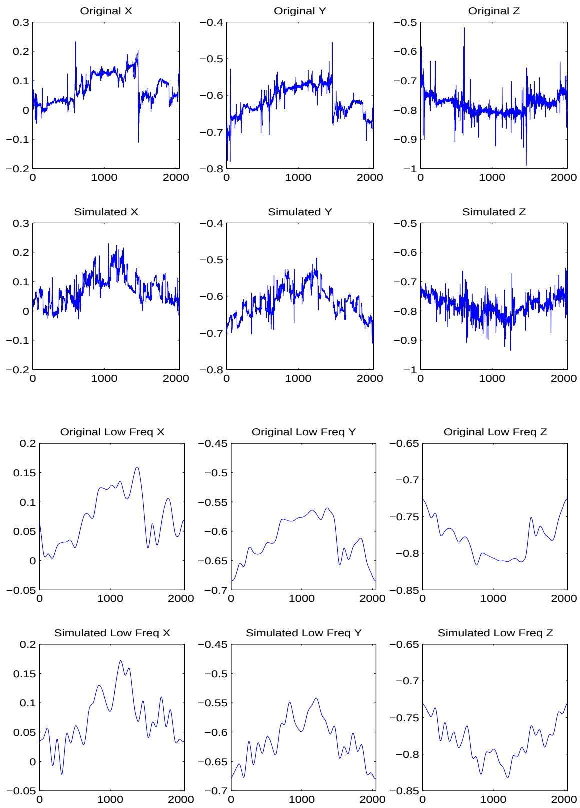


Figure 9: Original signal and simulated signal after trend and energy adjustments: the whole signal (top six) and the low frequency part (bottom six).

In addition, the idea of replacing scaling coefficients can be extended to other procedures, including the use of scaling exponents extracted from similar or related datasets (e.g., from other subjects, from similar studies, from existing databases). Instead of using the scaling coefficients of the original data, those of another subject's data could be used. An example is shown in Figure 10. This switching of the scaling coefficients implies that the variability in the simulated data can be stretched through the combination of data from multiple subjects. For example, if n samples are collected, then $\frac{n(n-1)}{2}$ combinations can be generated.

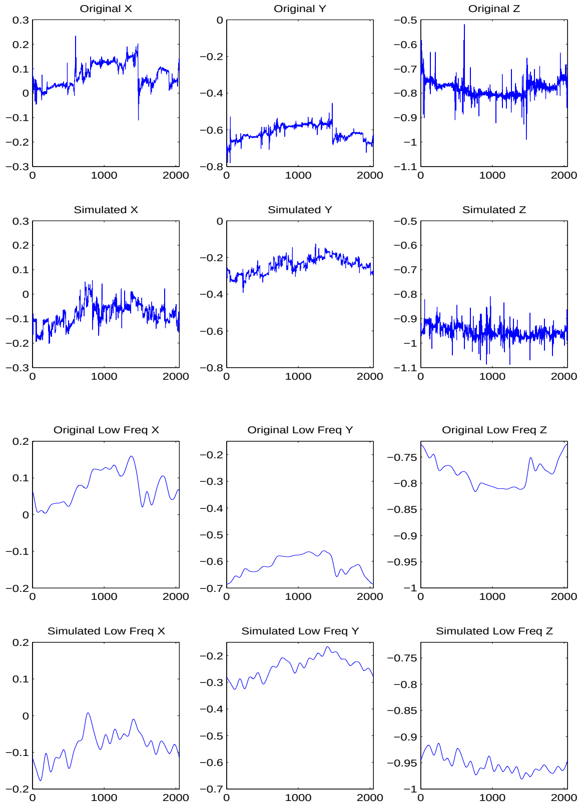


Figure 10: Original signal and simulated signal after replacement of scaling coefficients with those of other subject and energy adjustments: the whole signal (top six) and the low frequency part (bottom six).

4 Conclusions

Simulating the acceleration data that were collected in the mobile context is not a trivial task because they are non-stationary. Although several previous wavelet-based approaches have dealt with some critical characteristics of time series data and have served as efficient tools for simulating this complex time series data, some obstacles emerged when these approaches were applied to our collected acceleration data. First, the vertical correlation of wavelet coefficients among scale levels were not adequately accounted for in the prior wavelet-based approaches, which yields less disruptive surrogate data. Second, since the block length of the wavestrap method cannot cover the general trend of the original data adequately, the general trend of the acceleration data can be broken.

The first problem was resolved through the proposed level-wise parallel stationary bootstrapping. By this method, the vertical relationship among levels could be preserved since the scaling and wavelet coefficients on the same time frame are resampled together. The second problem was overcome by the proposed adjustment techniques. The broken general trends could be recovered via resampling by replacing the scaling coefficients of surrogate data with those of the original data. Additionally, the average energy for each scale level was adjusted according to the group mean of average energy to make the surrogate data possess the group scaling characteristics.

In conclusion, by using the proposed two-step wavestrap method, one could generate multiple runs of acceleration data accounting for various contextual situations. This application would be more important when collecting a single run of acceleration is expensive, such as the movement of mobile devices within military contexts or medical emergency situations, which represent usage contexts in which collecting actual data may be impossible or undesirable and collecting data via controlled experiments may be prohibitively expensive or difficult.

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